AGENT-BASED SIMULATION OF HURRICANE RISK INFORMATION DISSEMINATION

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The effectiveness of official warning dissemination and interpretation determines the adoption of protective actions in response to hurricane threat. This paper describes the development of a conceptual warning diffusion model that articulates the whole process of the hurricane warning diffusion and individual decision-making, drawing on emergency management and social science bodies of literature. This conceptual model is then partially encoded into a NetLogo agent-based simulation model to demonstrate the effects of various warning diffusion components on evacuation decisions for areas of interest. The translation of the conceptual model into agent-based simulations can inform the coastal engineering and science communities of the importance of communicating risk information to the public, and also helps to identify future research needed to illuminate hurricane risk communication pathways.

Keywords: hurricane warning dissemination; agent-based modeling; coastal storm risk

INTRODUCTION

Background and motivation

The process by which coastal storm risk information is developed and disseminated from experts through a community is a critical aspect of storm preparation. Understanding this dissemination process and the impact its components have on community protective action taking (such as evacuation) can help coastal scientists and engineers improve messaging around storm risk. Social scientists have provided models to explain and predict people's perceptions and behaviors in response to hurricanes. Some of these use empirical data and statistical tools to formulate warning diffusion speed and distribution (Lindell et al., 2021; Sorensen et al., 2000, 2020), while others stress the importance of known social dynamics in warning message uptake, such as trust in government reliability (Shao et al., 2017a; Cordasco et al., 2007), peer pressure from one's social network (Linardi, 2016; Hao and Shao, 2022; Eisenman et al., 2007; Ersing et al., 2020), crying wolf phenomenon (Dillon et al., 2011; Dillon and Tinsley, 2016), and ideological tendencies (Shao and Hao, 2021).

Chen et al. (2023, in review) have developed a conceptual model framework which attempts to encapsulate the full hurricane warning diffusion process, from the development of an official warning through the distribution of individual protective action taking. This conceptual model extends the theoretical framework developed by Mileti and Sorenson (1987, 1990) through an emphasis on formal and informal warning channels. The purpose of this paper is to present this conceptual model and its application to an agent based model (ABM) framework which can be used to simulate hurricane warning diffusion scenarios for areas of interest. This framework can be used in risk communication, evacuation decision modeling, and long-term hazard adjustment. This model can serve as a guideline for empirical behavior research of organizations, households, and individuals; simulation research for warning strategies; and practical applications for policies and planning for both response and long-term adjustment. It also can be used to guide long term hazard adjustment programs to increase effectiveness, due to the limited resources before a crisis and limited time during a crisis (Lindell and Perry, 2004).

Understanding the warning process and protective action taking

Individuals and households undergo a complex process of judging information and making decisions about how to respond to severe weather warnings. Factors a household may consider in deciding whether to evacuate can include warning severity, such as a hurricane Saffir-Simpson category scale; whether they trust the reasoning and motivation of the warning source; access to transportation; money available to travel and need to potentially pay for lodging, which might be dependent on whether they had to evacuate for a previous event; ability to take time away from work or caregiving responsibilities; the evacuation decisions of those around them; and their own tolerance for risk.

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A recent rapid-response study examined evacuation behavior during Hurricane Ida in 2021, including the effects of the Covid-19 pandemic on evacuation decisions (Polen et al., 2022). A survey of 124 individuals in the path of Ida, which was a Category 4 hurricane, found that 44% of them chose not to evacuate, including 35% who were under a voluntary evacuation order and 54% of those who were not under evacuation orders. 22% of those surveyed who did not evacuate said that caring for someone who could not or would not leave affected their decision. 65.7% of respondents who did not evacuate said that their pet played a role in that decision. The additional complexity of evacuating during the COVID-19 pandemic greatly affected individual evacuation decisions; Polen et al. (2022) found that respondents were less likely to consider evacuating to a public shelter than before the pandemic. Individuals navigating complex multi-hazard risks, such as a hurricane and a public health crisis, must receive and interpret information from multiple sources. The Hurricane Ida study found that respondents reported "lacking enough information to make 'a good evacuation decision'" by 10 percentage points compared to hurricanes in the same area prior to COVID-19 (Polen et al., 2022).

CONCEPTUAL MODEL FOR HURRICANE WARNING DIFFUSION

Development

A framework for understanding the dissemination of hurricane warning information and the processes by which individuals encounter, accept, or reject that information can be useful in emergency management planning. It can also be used to guide the development of storm risk information and the communication between expert scientific communities, emergency managers, and the general public. The conceptual model proposed here builds upon the Warning Response Model (Mileti and Sorensen, 1990; Sorensen and Richardson, 1984), Rogers and Sorensen's (1988) multi-channel warning dissemination model, Sorensen's (2000; Sorensen and Sorensen, 2007) characterization of effect sizes, as well as the Protective Action Decision Model (Lindell, 2018; Lindell and Perry, 1992, 2004, 2012) and recent summaries of research on hurricane evacuation decision making (Lindell et al., 2020, 2021; Sorensen et al., 2020). The goal is to fully articulate the processes between issuance of the official hurricane warning, through the ultimate decisions of individuals to evacuate or not across a distributed area. The framework can be modified for additional protective action decisions as more quantitative information about those decisions becomes available.

Components

The conceptual model framework (described fully in Chen et al., 2023; in review) divides the hurricane warning dissemination process into five major components: the official warning process, psychological and behavioral processes, observations, household characteristics, and informal warning processes. Each of these contains various subprocesses which have been described in the literature, and interactions occur bidirectionally between most of these components, as illustrated in Figure 1. The individual protective action decisions (i.e., decision to evacuate or not) occur within the psychological and behavioral processes component. These decisions can then influence the decisions of others through the informal warning process, and the observation process (such as an individual noticing neighbors evacuating).

The official warning process initiates the model, as in Mileti and Sorensen's (1987) hazard detection subsystem. The National Hurricane Center detects the presence of a hazard and characterizes the hazard through observations and estimates of wind speed, projected storm surge, and projected landfall location and inland flooding threats (Mileti and Sorensen, 1990). These assessments then inform local emergency management officials in issuing official warnings to the population at risk (Lindell et al., 2021). Multiple subprocesses govern this issuance of the official warning, including a desire by local authorities to discourage shadow evacuation (evacuation by those outside of the threat area, Lindell et al., 2019b), and to maintain credibility (Dow and Cutter, 1998). Official warnings are often characterized by physical parameters such as the estimated time to landfall, hurricane track and expected landfall location, and estimates of severity such as the Saffir-Simpson Category (Lindell and Prater, 2007a). Uncertainty is inherent in forecasting these conditions, and officials face a tradeoff between increasing warning time and increasing certainty. Local emergency managers may use evacuation timing arc models to determine when to issue decisions such as school closures or evacuation orders (Huang et al., 2017b; Sorensen et al., 2020).

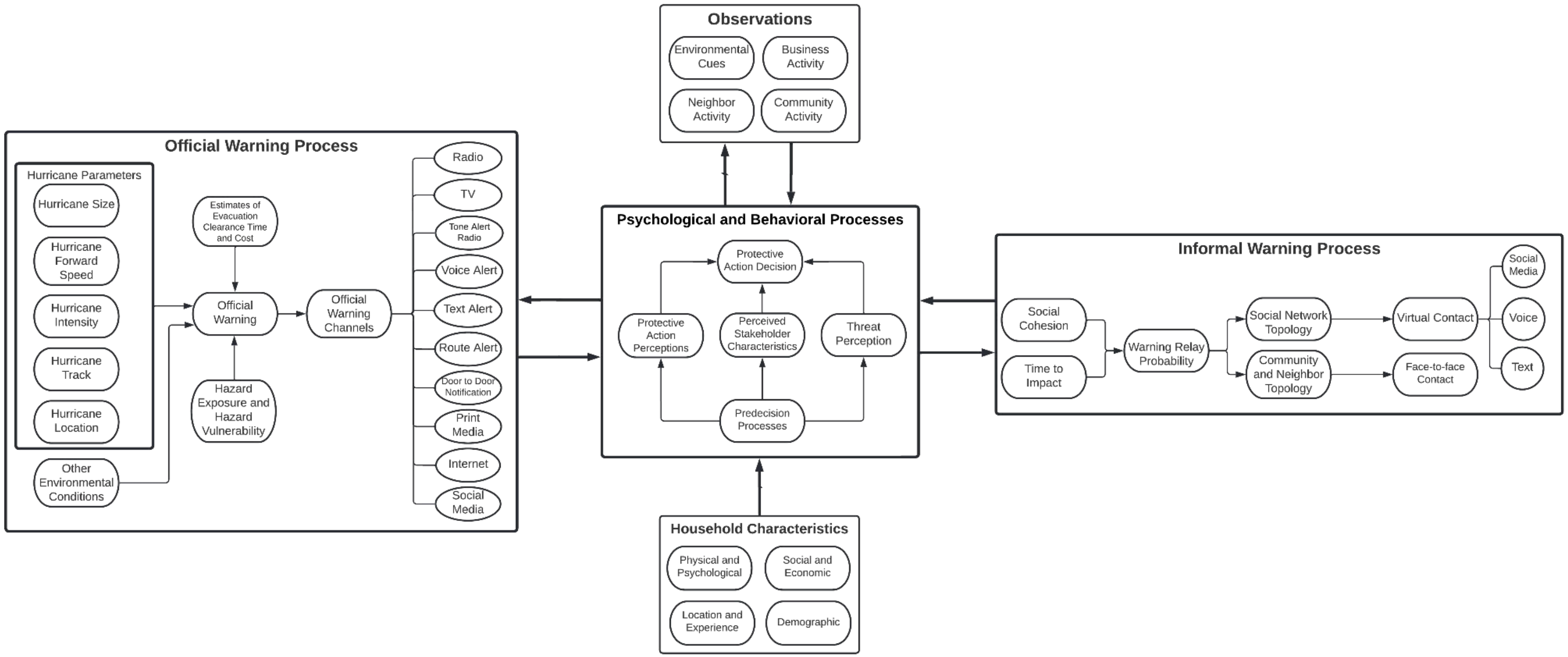

Figure 1. Hurricane warning dissemination conceptual model.

The official warning issuance component also includes consideration of what channels are used to communicate the official warning, including broadcast television, internet sites, official social media, and text alerts. Warning channels vary in dissemination speed, message precision, and distribution across the public (Lindell and Perry, 1992; Lindell and Prater, 2010; Lazo et al., 2015). Various demographics may be more or less likely to encounter or respond to different message channels. For example, DeYoung et al. (2016) found that nonwhite respondents preferred to receive warning message from local authorities compared to white respondents, and women and younger respondents tended to rely on multiple sources of warning while older respondents and men were more likely to rely upon a single source.

The population's response to this official warning and threat description is described in the Protective Action Decision Model (PADM, Lindell, 2018; Lindell and Perry, 1992, 2004, 2012). The Behavioral and Psychological Processes component of this conceptual model incorporates the PADM. Individuals must be exposed to, heed (notice), and comprehend warning information before a decision about protective action can be made (Lindell and Perry, 2004, 2012). Decisions are influenced by perceptions of the stakeholders who issue warning information: are local authorities considered expert and trustworthy (Arlikatti et al., 2007)? Decisions are also influenced by individuals' perceptions of threat severity and the efficacy of available protective actions. For a hurricane, people might consider the consequences of evacuating and leaving their home untended, or the possibility of traffic accidents (Huang et al., 2017a).

Informal warning processes are affected by individuals' decisions and also influence others' decisions, as noted by the bidirectional arrows between the Psychological and Behavioral Processes and the Informal Warning Processes components in Figure 1. Informal warning refers to warnings relayed between peers, including friends, family members, neighbors, and coworkers. Individuals have different propensities to relaying warnings to others, which are partially functions of cohesion within a community and the severity of a hazard (Hasan and Ukkusuri, 2011, 2013; Gladwin et al., 2007). Channels of informal warning include face-to-face (Lindell, 2018; Mileti and Sorensen, 1990), text or phone call, or via social media. Social media posts may have the furthest reach within peer networks (Dong et al., 2013), but may be perceived as less reliable sources of information (Wei et al., 2018).

Observations of the environment are another source of information that individuals factor into their decisions to take protective action in the face of hurricane hazards (Lindell et al., 2005). Observations include perceptions of weather or behavior of the ocean, as well as witnessing others evacuating and businesses closing (Huang et al., 2016). The conceptual model of hurricane warning diffusion includes reciprocal interaction between the Psychological and Behavioral Processes and the Observation components (Figure 1), since some individuals' decisions to prepare and evacuate can influence the decisions of those who witness their actions.

The final component of the conceptual model is Household Characteristics, which includes information about individuals' resources, physical and psychological variables, and demographic variables. These characteristics can affect aspects of the PADM, including where individuals search for information about a hazard and their perceptions about stakeholders and information sources (Lindell and Perry, 2012) and their tendency to relay warnings to their peers (Perry et al., 1981). Tenure in a hazard zone and prior experience with hazards can also factor into decision-making (Bostrom et al., 2018). Education and income levels can influence awareness of environmental risks (Kim et al., 2019; Shao et al., 2014).

AGENT-BASED MODEL FOR WARNING ACCEPTANCE

Development in NetLogo

The conceptual model defined in Figure 1 was implemented into an ABM in the program NetLogo (Wilensky, 1999) to enable simulations of hurricane warning diffusion scenarios for areas of interest. ABMs have been used in prior simulations of hurricane response (Yin et al., 2014, 2016; Gao and Wang, 2021; Harris et al., 2022). Use of ABMs in understanding hurricane warning diffusion in a population might support improved practices in risk communication and hazard planning. Simulations begin with the detection of the hazard and conclude with landfall, and the outcomes include the number of area residents informed of the warning disaggregated by warning channel, and the probabilities of warning acceptance and protective action implementation in the different hurricane risk zones and for different demographic groups along hourly intervals. Figure 2 shows the ABM interface in NetLogo, including the variable control bars, model parameter monitors, and outcome map and monitors, for a simulation in Baldwin County, Alabama of a Category 3 hurricane.

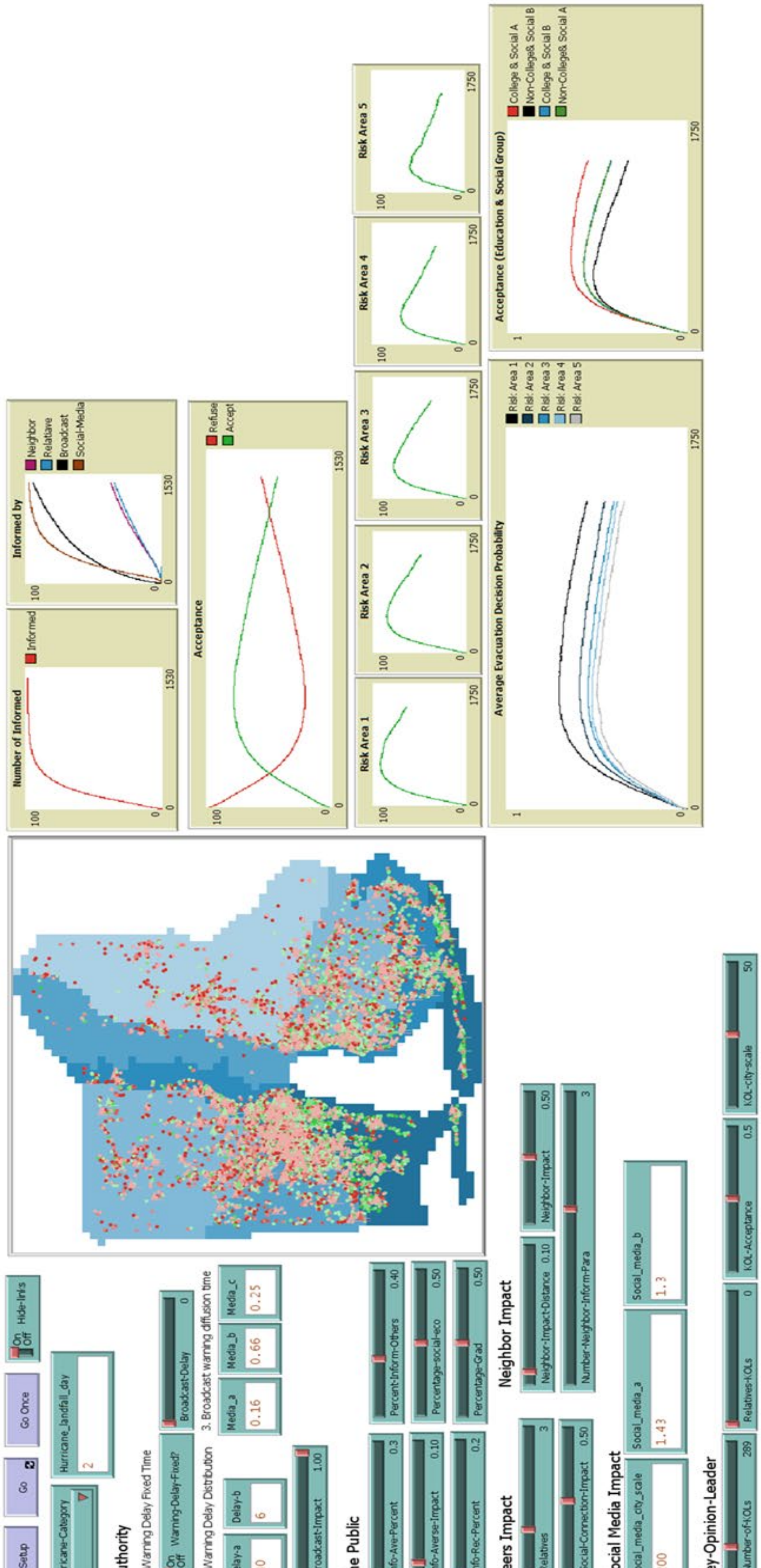

Figure 2. ABM interface in NetLogo.

The components of the conceptual model outlined in Figure 1 are implemented into the ABM using available quantitative relationships, as detailed further in Chen et al. (2023, in review). These components are presented below by component of the conceptual framework in Table 1.

Table 1. Formulation of available hurricane risk diffusion processes included in the ABM.

Framework component	Formulation and references
Official warning processes	• Relationships between the hurricane Saffir Simpson scale and expected evacuation rates by risk zone (Lindell and Prater, 2007b) • Official warning delay time as a function of mean times and random probability (Sorensen et al., 2020) • Proportion of the population receiving the warning at time *t* as a function of community and channel parameters (Lindell et al., 2021)
Informal warning processes	• Probability of contact between peers by phone call and by text (Lindell et al., 2021) • Warning relay via social media as a Weibull distribution function of community cohesion via Facebook connectivity data (Wolfram, 2013) • Probability of individuals accessing social media (Lindell et al., 2021) • Probability of contact between neighbors (Lindell et al., 2021) • Face to face contact between neighbors as a function of physical distance • Distance individuals are likely to travel to warn a neighbor (Katada et al., 1999; Zhang et al., 2014)
Observations	• Individual observation of environmental cues, as controlled by a user slider interface
Psychological and Behavioral Responses and Personal Characteristics	• Linear regression of warning acceptance by education level (Huang et al., 2012) • Linear regression of warning acceptance by social group (Huang et al., 2016, 2017a)

Data availability to populate the components of the ABM is a major limitation of this work. The conceptual model detailed in Figure 1 has many processes that are not represented in the ABM, and those that are included use quantitative relationships based off of few limited studies.

Simulations

Sensitivity analyses can be conducted by changing the variables in the control bars. Users can select a hurricane category for a simulation (based on the Saffir-Simpson scale) that impacts the warning process in the different hurricane evacuation zones for the area of interest. Other variables that can be tuned for simulation include the hurricane landfall day from initial detection, official warning delay time, parameters for warning dissemination speeds, the effectiveness of the official warning, the distribution of individual social network sizes (neighbors and/or relatives), the impact of social connections, impact of social media, number of key-opinion-leaders (KOLs, members of the community with increased influence over others) and their impact, coefficients of ideological variables (such as information aversion), distribution of individual education levels, and individual political preference. The outcome monitors allow users to observe the warning dissemination speed within each warning channel and the probability of acceptance of protective actions in different hurricane evacuation zones, and for different demographic groups.

Depending on the input variables selected, the acceptance of protective action is dynamic during the warning process simulation. For example, an individual who rejected the evacuation order at the beginning may decide to obey the order later on after being influenced by peers and social media. Figure 3 shows the visualization of the dynamic process of one scenario in Baldwin County, Alabama for a

Category 2 hurricane. The colored dots on the map indicate individuals in the simulation, and their color represents likelihood of deciding to evacuate at each timestep in the simulation. In Figure 3, the simulation depicts an initial increase in decisions to evacuate from the 0 hour timestep through 10 hours after the official warning. However, individuals in the simulation start to hesitate and change their minds, reverting to a rejection of the official evacuation advisory due to the influence of social connections and KOLs. It should be noted that this scenario demonstrates the dynamic process of people's evacuation decisions, but it does not reflect other scenarios when changing impact variables. Additionally, this ABM does not allow for the incorporation of changing conditions during the simulation, such as a hurricane forecast being downgraded in category or projecting a change in landfall location, but it is possible to chain together simulations with different initial conditions to reflect these types of changing scenarios.

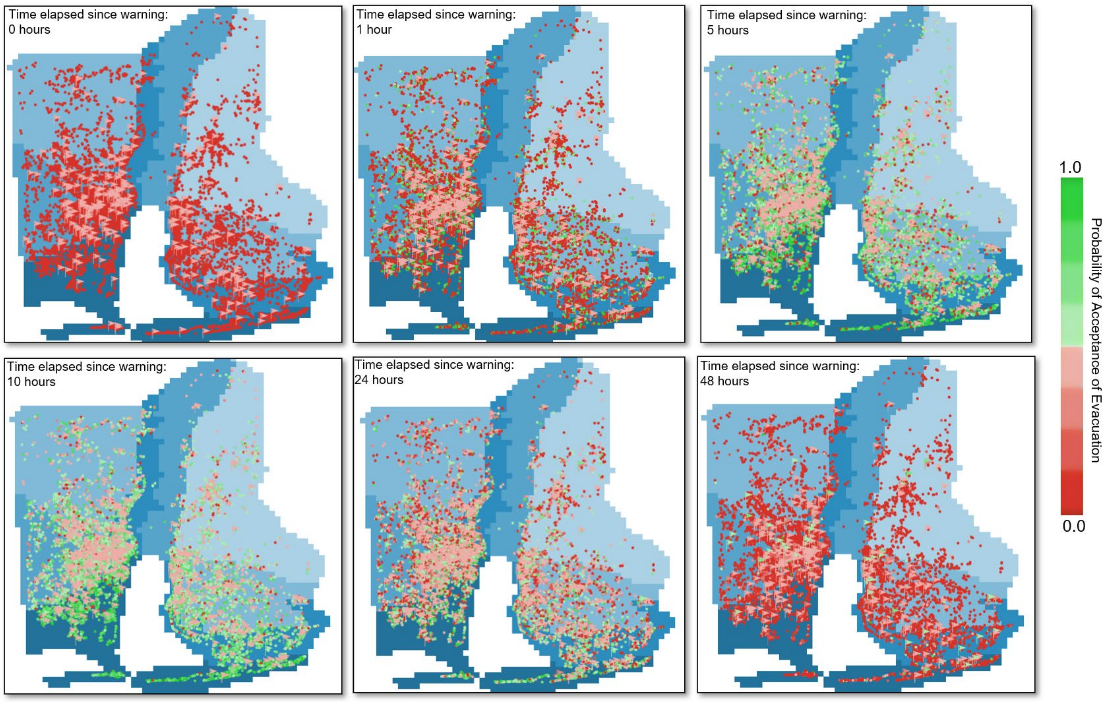

Figure 3. Probability of warning acceptance over time for Baldwin County, Alabama simulation.

Figure 4 shows the cumulative percentage of people who received warning information through different channels during an entire simulation. While the official broadcast (via TV, radio, or other traditional media) has a faster warning speed than other channels, the social media transmission speed increases faster and eventually surpasses the percentage of people warned by an official warning. The rate of individuals informed by neighbors and relatives is much lower, as face-to-face and phone call warning transmissions only occur between two individuals at a time. This is consistent with previous findings that people have a limitation of how far away they are willing to travel to inform their neighbors about a hazard (Katada et al., 1999; Zhang et al., 2014). The social connectivity in the current model is based on Facebook connectivity data but can be tuned for sensitivity analyses (Wolfram, 2013).

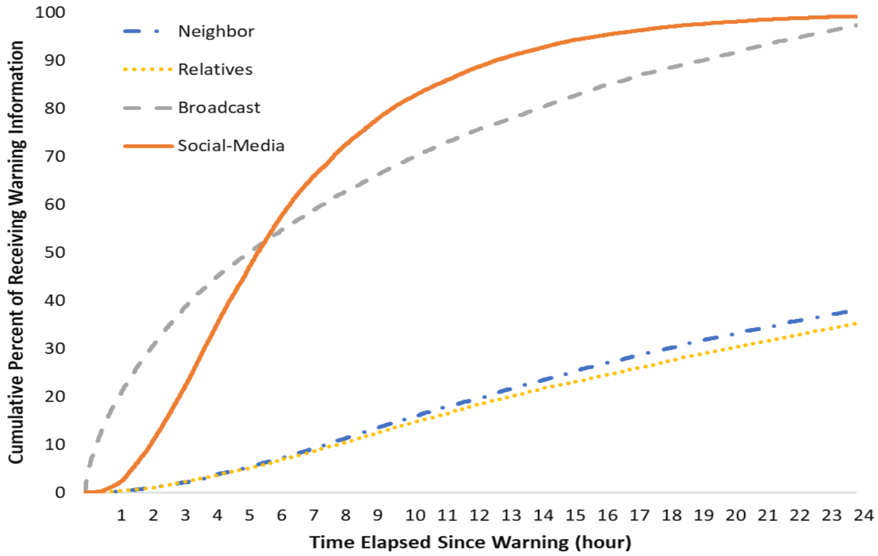

Figure 4. Cumulative percent of warning receipt by information channel over time for Baldwin County, Alabama simulation.

The distribution of social connectedness of individuals within a community can be tuned within the ABM. To test the impact of social connection, a series of sensitivity analyses was conducted on this factor. Figure 5 shows that the average probability of complying with the official evacuation order significantly differs in five hurricane evacuation zones. However, by increasing the social connection parameter (along the x-axis in Figure 5), a consensus situation was reached across the different geographic hurricane risk zones. Stronger social connection across the community reduces the importance of individual's locations in determining whether they will take protective actions in the simulation. Higher social connectedness means that individuals are more likely to follow the decisions of their peers, which can spread across the hurricane risk zones. While this model scenario cannot fully represent a real hazard situation, a "tipping" point can be observed when the social connection impact is 0.3, after which decisions converge across zones. It should be noted that the tipping point may vary while changing other variables, such as hurricane categories. Sensitivity testing of the ABM can lead to more realistic settings for parameters such as social connectedness, which are difficult to base on real data for every area.

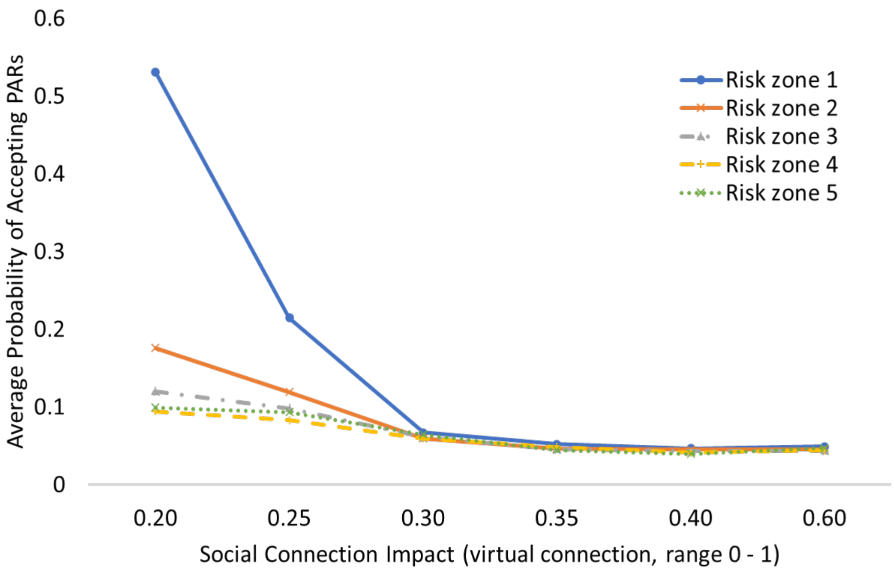

Figure 5. Impact of social connection on Protective Action Taking acceptance rates by risk zone.

Figure 6 shows the impact of the number of KOLs on rates of individuals accepting a warning and choosing to evacuate, by hurricane risk zone. KOLs might include local media personalities, church leaders, social media influencers, and others with significant sway in their community. Risk zone 1 has a higher acceptance rate than other risk zones. This scenario demonstrates that an increase of the KOLs supporting the evacuation decision results in the increase of evacuation order compliance rate. The compliance rate increases the most when the KOL number increases from 0 to 80 within the community. After that, the impact of an increase in the KOL number decreases where its effect is negligible from 160 – 280 KOLs. This finding is also consistent with another warning study that the impact of official warning increases rapidly at the beginning and then declines significantly later (Koll et al., 2023). While we conducted a sensitivity analysis on the KOL number, future research could use real social data to analyze the “leader-follower” effect (King and Cowlishaw, 2009).

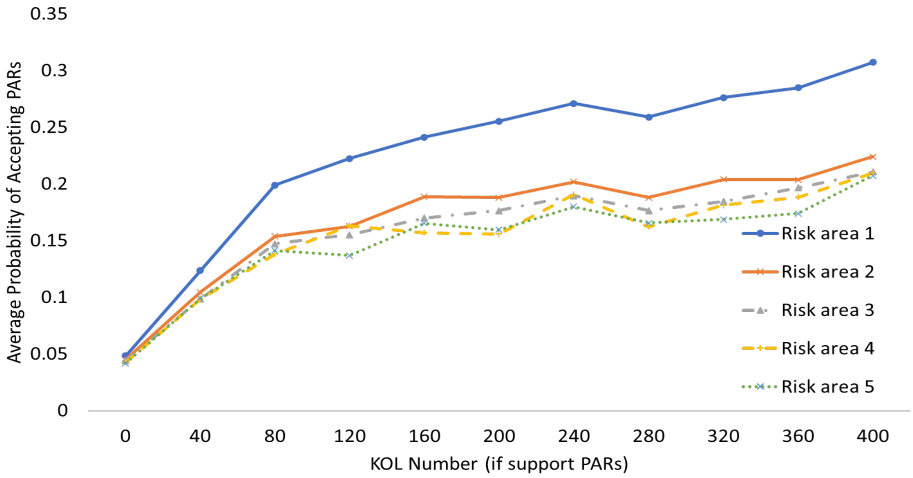

Figure 6. Impact of Key Opinion Leaders on Protective Action Taking acceptance rates by risk zone.

CONCLUSIONS

Early evacuation simulation studies were problematic because they focused on the transportation process and modeled the warning dissemination process, a critical part of the ETE components, by using assumptions or simplified mathematical distributions (Lindell and Perry, 1992; Lindell and Prater, 2007b). However, those simplifications lose the opportunity to test the variables that impact warning dissemination distributions, such as ideological variables, authorities’ decisions, and social network connectivity. To fill the gaps, this study created an ABM for hurricane warning dissemination that accounts for both official and unofficial warning channels—including official broadcast, new media, face-to-face contact, and virtual contact—as well as observation of environmental and social cues. Based on cumulative empirical warning studies from the last several decades, the ABM combines a social science framework with current social media data into an interdisciplinary simulation platform. This model can be used to identify factors that impact warning dissemination speed, test authorities’ warning strategies, increase the accuracy of evacuation transportation analyses, and test the impact of societal changes in communication technologies. The results show that protective decision as a dynamic process can be impacted by variables such as social connectivity, peer pressure, ideological intention, and proxy to hazards. “Tipping” points were observed in the social connectedness and KOL analysis, which indicates a phenomenon that social media influencers can impact protective decisions. While this model can be generalized to other situations, the data input is mainly from U.S. hurricanes, so adopting the model to other countries and other hazards will require local data justification. Future studies can extend and validate the simulation model using empirical hurricane warning data, i.e., phone-based social media data or questionnaire survey data. More social science studies are also needed to assess the impact of different variables on the analysis results, such as the influencers and leader-follower effects.

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REFERENCES

Arlikatti, S., M.K. Lindell, and C. Prater. 2007. Perceived stakeholder role relationships and adoption of seismic hazard adjustments. *International Journal of Mass Emergencies and Disasters*, 25(3), 218–256.

Bostrom, A., R. Morss, J.K. Lazo, J. Demuth, and H. Lazrus. 2018. Eyeing the storm: How residents of coastal Florida see hurricane forecasts and warnings. *International Journal of Disaster Risk Reduction*, 30, 105-119.

Chen C., M.K. Lindell, E.M. Yeates, M.J. Shaw, and W. Shao. 2023. Hurricane Risk Information Dissemination Model: Theoretical formulation and evidence. *Natural Hazards Review*. (*in review*).

Cordasco, K.M., D.P. Eisenman, D.C. Glik, J.F. Golden, and S.M. Asch. 2007. "They blew the levee": Distrust of authorities among Hurricane Katrina evacuees. *Journal of Health Care for the Poor and Underserved*, 18(2), 277-282.

DeYoung, S.E., T. Wachtendorf, A.K. Farmer, and S.C. Penta. 2016. NOAA radios and neighbourhood networks: Demographic factors for channel preference for hurricane evacuation information. *Journal of Contingencies and Crisis Management*, 24(4), 275-285.

Dillon, R.L., C.H. Tinsley, and M. Cronin. 2011. Why near-miss events can decrease an individual's protective response to hurricanes: Near-misses and protective responses to hurricanes. *Risk Analysis*, 31(3), 440–449. https://doi.org/10.1111/j.1539-6924.2010.01506.x

Dillon, R.L., and C.H. Tinsley. 2016. Near-miss events, risk messages, and decision making. *Environment Systems and Decisions*, 36(1), 34–44. https://doi.org/10.1007/s10669-015-9578-x

Dong, H., M. Halem, and S. Zhou. 2013. Social media data analytics applied to Hurricane Sandy. *International Conference on Social Computing* (pp. 963-966). IEEE.

Dow, K., and S.L. Cutter. 1998. Crying Wolf: Repeat responses to hurricane evacuation orders. *Coastal Management*, 26(4), 237–252. https://doi.org/10.1080/08920759809362356

Eisenman, D.P., K.M. Cordasco, S. Asch, J.F. Golden, and D. Glik. 2007. Disaster planning and risk communication with vulnerable communities: lessons from Hurricane Katrina. *American Journal of Public Health*, 97 (Supplement_1), S109-S115

Ersing, R., C. Pearce, J.M. Collins, M.E. Saunders, and A. Polen. 2020. Geophysical and social influences on evacuation decision-making: The case of Hurricane Irma. *School of Geosciences Faculty and Staff Publications*. 2230. https://digitalcommons.usf.edu/geo_facpub/2230.

Gao, S., and Y. Wang. 2021. Assessing the impact of geo-targeted warning messages on residents' evacuation decisions before a hurricane using agent-based modeling. *Natural Hazards*, 107(1), 123-146.

Gladwin, H., J.K. Lazo, B.H. Morrow, W.G. Peacock, and H.E. Willoughby. 2007. Social science research needs for the hurricane forecast and warning system. *Natural Hazards Review*, 8(3), 87-95.

Hao, F., and W. Shao. 2022. Understanding the influence of political orientation, social network, and economic recovery on COVID-19 vaccine uptake among Americans. *Vaccine*, 40(14), 2191–2201. https://doi.org/10.1016/j.vaccine.2022.02.066

Harris, A., P. Roebber, and R. Morss. 2022. An agent-based modeling framework for examining the dynamics of the hurricane-forecast-evacuation system. *International Journal of Disaster Risk Reduction*, 67, 102669. https://doi.org/10.1016/j.ijdrr.2021.102669

Hasan, S., R. Mesa-Arango, and S. Ukkusuri. 2013. A random-parameter hazard-based model to understand household evacuation timing behavior. *Transportation Research Part C: Emerging Technologies*, 27, 108-116.

Hasan, S., and S. Ukkusuri. 2011. A threshold model of social contagion process for evacuation decision making. *Transportation Research Part B: Methodological*, 45(10), 1590-1605.

Hasan, S., and S. Ukkusuri. 2013. Social contagion process in informal warning networks to understand evacuation timing behavior. *Journal of Public Health Management and Practice*, 19, S68-S69, DOI: 10.1097/PHH.0b013e31828f1a19

Huang, S.-K., M.K. Lindell, C.S. Prater, H.-C. Wu, and L.K. Siebeneck. 2012. Household evacuation decision making in response to Hurricane Ike. *Natural Hazards Review*, 13(4), 283–296. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000074

Huang, S.-K., M.K. Lindell, and C.S. Prater. 2016. Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. *Environment and Behavior*, 48(8), 991–1029. https://doi.org/10.1177/0013916515578485

Huang, S.-K., M.K. Lindell, and C.S. Prater. 2017a. Multistage model of hurricane evacuation decision: Empirical study of Hurricanes Katrina and Rita. *Natural Hazards Review*, 18(3), 05016008. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000237

Huang, S-K., M.K. Lindell, H-L. Wei, and C.D. Samuelson. 2017b. Perceptions, behavioral expectations, and implementation timing for response actions in a hurricane emergency. *Natural Hazards*, 88(1), 533-558. DOI 10.1007/s11069-017-2877-4.

Katada, T., Y. Oikawa, and T. Tanaka. 1999. Development of simulation model for evaluating the efficiency of disaster information dissemination. *Doboku Gakkai Ronbunshu*, (625), 1–13. (In Japanese). https://doi.org/10.2208/jscej.1999.625.

Kim, S., W. Shao, and J. Kam. 2019. Spatiotemporal patterns of US drought awareness. *Palgrave Communications*, 5(1), 107. https://doi.org/10.1057/s41599-019-0317-7.

King J.A. and G. Cowlishaw. 2009. Leaders, followers, and group decision-making. *Communicative and Integrative Biology*, 2:2, 147-150.

Koll, C., M.K. Lindell, C. Chen, and H. Wang. 2023. Emergency warning dissemination in a multiplex social network. *Journal of Artificial Societies and Social Simulation*, 26(1) 7. Doi: 10.18564/jasss.4946

Lazo, J.K., A. Bostrom, R.E. Morss, J.L. Demuth, and H. Lazrus. 201). Factors affecting hurricane evacuation intentions. *Risk Analysis*, 35(10), 1837-1857.

Linardi, S. 2016. Peer coordination and communication following disaster warnings: An experimental framework. *Safety Science*, 90, 24-32.

Lindell, M. K. 2018. Communicating Imminent Risk. In H. Rodríguez, W. Donner, and J. E. Trainor (Eds.), *Handbook of Disaster Research* (pp. 449–477). Springer International Publishing. https://doi.org/10.1007/978-3-319-63254-4_22

Lindell, M.K., S. Arlikatti. and S-K. Huang. 2019. Immediate behavioral response to the June 17, 2013 flash floods in Uttarakhand, North India. *International Journal of Disaster Risk Reduction*, 34, 129-146. DOI: 10.1016/j.ijdrr.2018.11.011.

Lindell, M.K., J.C. Lu, and C.S. Prater. 2005. Household decision making and evacuation in response to Hurricane Lili. *Natural Hazards Review*, 6, 171-179.

Lindell, M.K., P. Murray-Tuite, B. Wolshon, and E.J. Baker. 2019b. *Large-scale Evacuation: The Analysis, Modeling, and Management of Emergency Relocation from Hazardous Areas*. New York: Routledge.

Lindell, M.K., and R.W. Perry. 1992. *Behavioral Foundations of Community Emergency Planning*. (pp. xi, 309). Washington DC: Hemisphere.

Lindell, M.K., and R.W. Perry. 2004. *Communicating Environmental Risk in Multiethnic Communities*. SAGE Publications, Inc. https://doi.org/10.4135/9781452229188

Lindell, M.K., and R.W. Perry. 2012. The protective action decision model: Theoretical modifications and additional evidence. *Risk Analysis*, 32(4), 616–632. https://doi.org/10.1111/j.1539-6924.2011.01647.x

Lindell, M.K. and C.S. Prater. 2007a. A hurricane evacuation management decision support system (EMDSS). *Natural Hazards*, 40, 627-634.

Lindell, M.K., and C.S. Prater. 2007b. Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: examples from hurricane research and planning. *Journal of Urban Planning and Developmen*t, 133(1), 18–29. https://doi.org/10.1061/(ASCE)0733-9488(2007)133:1(18)

Lindell, M.K. and C.S. Prater. 2010. Tsunami preparedness on the Oregon and Washington coast: Recommendations for research. *Natural Hazards Review*, 11, 69-81.

Mileti, D. S., and J.H. Sorensen. 1987. Natural hazards and precautionary behavior. In N.D. Weinstein (ed.). *Taking Care: Understanding and Encouraging Self-protective Behavior* (189-207). New York: Cambridge University Press.

Lindell, M.K., J.H. Sorensen, E.J. Baker, and W.P. Lehman. 2020. Community response to hurricane threat: Estimates of household evacuation preparation time distributions. *Transportation Research D: Transport and Environment*, 85, 102457. DOI: 10.1016/j_trd.2020.102457.

Lindell, M.K., J.H. Sorensen, E.J. Baker, and W.P. Lehman. 2021. Community response to hurricane threat: Estimates of warning diffusion time distributions. *Natural Hazards Review*, 22(2), 04021007. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000456

Mileti, D.S., and J.H. Sorensen. 1990. *Communication of emergency public warnings: A social science perspective and state-of-the-art assessment* (ORNL-6609). https://doi.org/10.2172/6137387

National Hurricane Center. (n.d.). Saffir-Simpson Hurricane Wind Scale. Retrieved April 11, 2022, from https://www.nhc.noaa.gov/aboutsshws.php

Perry, R.W., M.K. Lindell, and M.R. Greene. 1981. *Evacuation planning in emergency management*. Lexington MA: Lexington Books.

Polen, A., J. Collins, E. Dunn, S. Murphy, I. Jernigan, and K. McSweeney. 2022. The effect of COVID-19 vaccination on evacuation behavior during Hurricane Ida. *Natural Hazards Center Quick Response Grant Report Series*, 344. Boulder, CO: Natural Hazards Center, University of Colorado Boulder. Available at: https://hazards.colorado.edu/quick-response-report/the-effect-of-covid-19-vaccination-on-evacuation-behavior-during-hurricane-ida.

Rogers, G.O., and J.H. Sorensen. 1988. Diffusion of emergency warnings. *The Environmental Professional*, 10, 281–294.

Shao, W., and F. Hao. 2021. Understanding American public support for COVID-19 risk mitigation: The role of political orientation, socio-demographic characteristics, personal concern, and experience. *International Journal of Public Health*, 66. https://doi.org/10.3389/ijph.2021.160403

Shao, W., B.D. Keim, J.C. Garand, and L.C. Hamilton. 2014. Weather, climate, and the economy: Explaining risk perceptions of global warming, 2001–2010. *Weather, Climate, and Society*, 6(1), 119–134. https://doi.org/10.1175/WCAS-D-13-00029.1

Shao, W., S. Xian, N. Lin, and M.J. Small. 2017a. A sequential model to link contextual risk, perception, and public support for flood adaptation policy. *Water Research*, 122, 216–225. https://doi.org/10.1016/j.watres.2017.05.072

Sorensen, J. H. 2000. Hazard warning systems: Review of 20 years of progress. *Natural Hazards Review*, 1(2), 119–125. https://doi.org/10.1061/(ASCE)1527-6988(2000)1:2(119)

Sorensen, J.H., M.K. Lindell, E.J. Baker. and W.P. Lehman. 2020. Community response to hurricane threat: Estimates of warning issuance time distributions. *Weather, Climate and Society*, 12, 837-846. DOI: 10.1175/WCAS-D-20-0031.s1

Sorensen, J.H., and B. Richardson. 1984. Risk and uncertainty as determinants of human response in emergencies: Evacuation at TMI reexamined. In Proceeding of the *Annual Meeting of the Society for Risk Analysis*, Knoxville, TN.

Sorensen, J.H., and B.V. Sorensen. 2007. Community Processes: Warning and Evacuation. In H. Rodríguez, E. L. Quarantelli, and R. R. Dynes (Eds.), *Handbook of Disaster Research* (pp. 183–199). Springer. https://doi.org/10.1007/978-0-387-32353-4_11

Wei, H.-L., M.K. Lindell, C.S. Prater, J. Wei, F. Wang, and Y.G. Ge. 2018. Perceived stakeholder characteristics and protective action for influenza emergencies: A comparative study of respondents in the United States and China. *International Journal of Mass Emergencies and Disasters*, 36, 52–70.

Wilensky, U. 1999. *NetLogo*. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University. Evanston, IL.

Wolfram, 2013. *Data science of the Facebook world*. url: writings.stephenwolfram.com/2013/04/data-science-of-the-facebook-world/.

Yin, W., P. Murray-Tuite, S.V. Ukkusuri, and H. Gladwin. 2014. An agent-based modeling system for travel demand simulation for hurricane evacuation. *Transportation Research Part C: Emerging Technologies*, 42, 44-59.

Yin, W., P. Murray-Tuite, S.V. Ukkusuri, and H. Gladwin. 2016. Modeling shadow evacuation for hurricanes with random-parameter logit model. *Transportation Research Record*, 2599(1), 43-51.

Zhang, N., H. Huang, B. Su, J. Zhao, and B. Zhang. 2014. Information dissemination analysis of different media towards the application for disaster pre-warning. *PLoS ONE*, 9(5), e98649. https://doi.org/10.1371/journal.pone.0098649